The Golden Age of Social Science

Anastasia Buyalskaya[1], Marcos Gallo[1], Colin F. Camerer[1, 2]

[1]California Institute of Technology, Division of Humanities and Social Science
[2]California Institute of Technology, Computational and Neural Systems

12 November 2019. Preliminary. Comments welcome. Corresponding author Anastasia Buyalskaya (abuyalsk@caltech.edu).

1. Introduction

Social science is entering a golden age. A rise in effective interdisciplinarity, the explosive growth of available data and computational power to make that data useful, and an increasing realization that pressing social challenges require cooperation across disciplines, have all contributed to this opportune time. Figure 1 presents evidence from cross-citations of how interdisciplinary research is on the rise in some social sciences, although not uniformly. The historically most inward-looking social science disciplines -- psychology and economics, according to the Figure 1 data -- have become more open to the idea that researchers in neighboring fields have important information and methods to contribute to their disciplines. This opening of disciplinary borders is akin to an increasing "trade" of methods, languages, and knowledge across fields.

The application of economic language about trade begins with the premise that, like people and countries, each social science discipline has different "endowments" (e.g., historical mastery of tools and accumulated knowledge) and comparative advantage (e.g., anthropologists carefully study different parts of the world and economists develop formal models). Each discipline has a specialized view, and none can fully explain human nature on its own. Economics is endowed with a set of formal mathematical tools that all graduate students must master in order to make predictions based on optimization given preferences and beliefs, as well as an econometrics toolkit for testing theories and inferring causation. Psychology explores the rich web of cognitive and social mechanisms that generate individual beliefs and behaviors. Anthropology seeks to understand cultural differences using ethnographic observation, unearthing physical details of human development, and exploring mathematical models of coevolution of culture and genes (among other approaches), hoping one model may effectively approximate all human behavior at once. Political science studies systems of government, voting, juries, law, and a range of other situations in which people make consequential decisions collectively. Finally, sociology investigates how the social world is created by and influences how people think, feel, and act.

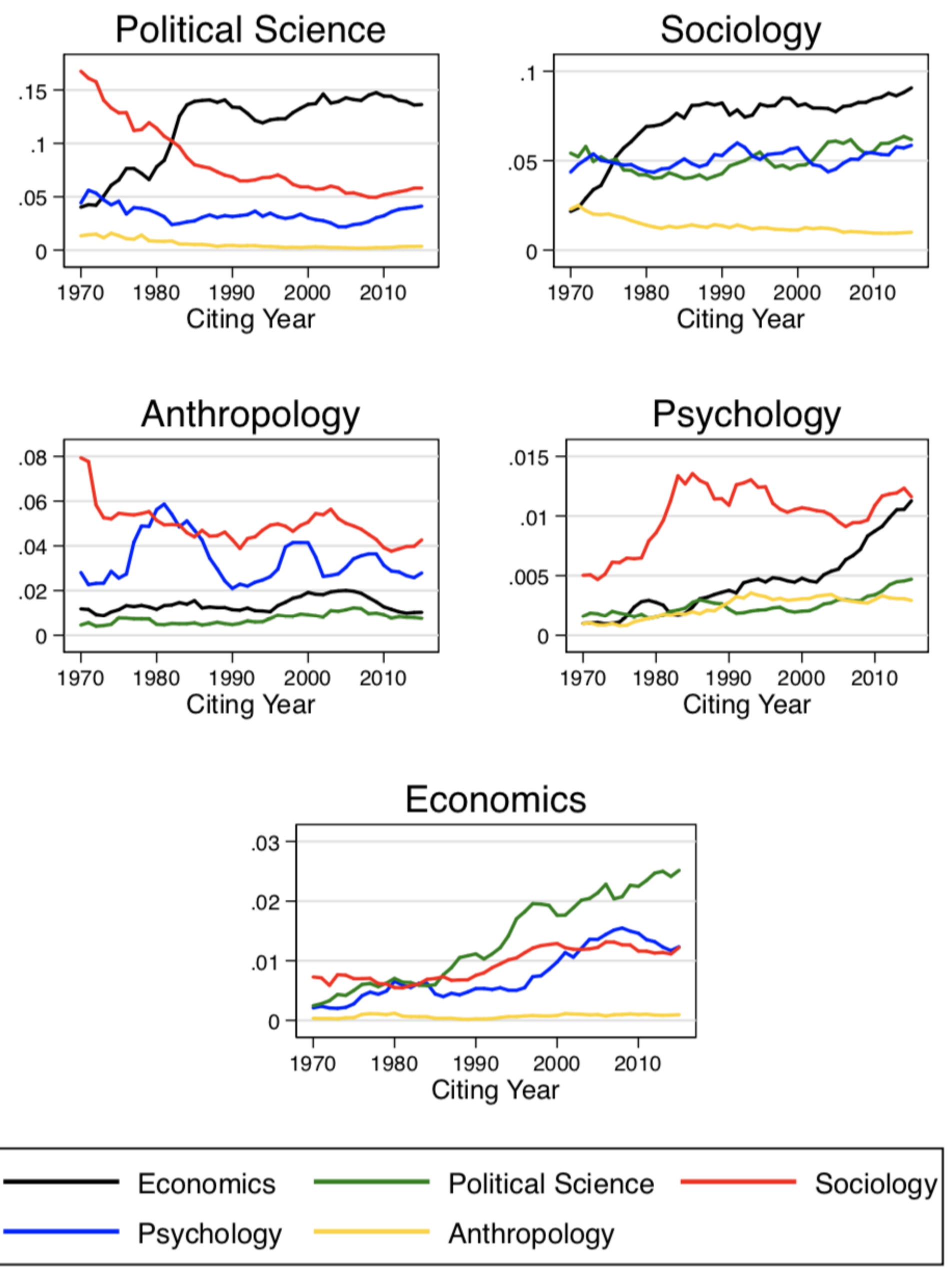

Figure 1: Changes in rates of imported citations from neighboring disciplines from 1970 to 2015 for five social science disciplines. Imported citations are generally increasing over this period, with notable exceptions (e.g., anthropology is not importing more citations and is not being imported either). Note the differences in y-axis ranges too: these show that

political science and sociology import a lot, but psychology and economics do not. The authors used weighted citation rates to observe changes in citation rates from the five social sciences to each of the other four. Plots are 5-year moving averages. Source: Angrist et al. (2017).

One of the challenges of interdisciplinary work is communication among researchers. Multiple fields may investigate the same behavior but be unable to communicate their methods in a manner digestible by all potential collaborators. Interdisciplinarity needs a common trade language across disciplines, a "lingua franca." In a useful lingua franca, all disciplines adopt the 'best' language from whichever discipline first described an idea or construct with language clear enough to be imported into a new discipline without much confusion. Working together to build a common vocabulary will enhance the efficiency of trade and collaboration.

Prominent examples of lingua franca include rational choice theory from economics, human laboratory experimental methods from psychology, culture from anthropology, survey methods in political science, social networks from sociology, and tools for causal inference from all over. Another notable example is game theory. Created by mathematicians such as John Nash, this framework only flourished after the seminal 1944 book by the polymath John von Neumann and the economist Oskar Morgenstern. Game theory is a lingua franca for social sciences because its basic concepts--players, information, strategies--are defined broadly enough to potentially apply to genes, viruses, insects, animals, and organizations with shared values, including nation-states (Gintis, 2007).

Most importantly, interdisciplinarity is necessary for solving complex multi-dimensional problems and creating innovations for better health, wealth, and well-being (Watts, 2017). Some of today's most significant and fastest-growing problems, such as drug addiction, obesity, changes in political discourse, and climate change, cannot be understood or solved by one discipline alone. Instead, solving these issues will require an understanding of the institutional incentives, cultural norms, cognitive mechanisms, and social network effects that created and continue to heavily influence these phenomena. Interdisciplinary work has already helped make progress in fields, including poverty, health epidemics, and mental health.

Drug trafficking is one such example of how an interdisciplinary approach can facilitate problem-solving. Magliocca et al. (2019) combined interdisciplinarity and new data to analyze international drug trafficking in Central America (Figure 2). The researchers tested an agent-based model against a database of estimated illicit drug flows from 2000-2014. In their model, the agents were local suppliers, cartel networks, and interdiction organizations trying to intercept drugs from the traffickers. The traffickers were motivated by profit, including a priced-in interdiction risk premium. Interdiction agents were motivated to intercept drugs (and interdiction capacity increased based on past success). Agent-based models seek to derive complex, lifelike behavior that is "emergent" from interactions of simple agents, typically simulating behavior which is too complex to solve mathematically. The model is successful at capturing many of the underlying trends, across time and countries, in trafficking flow and interdiction. It reproduces two effects known as the “balloon” effect (when trafficking spreads into new areas) and the “cockroach” effect (when trafficking routes become fragmented).

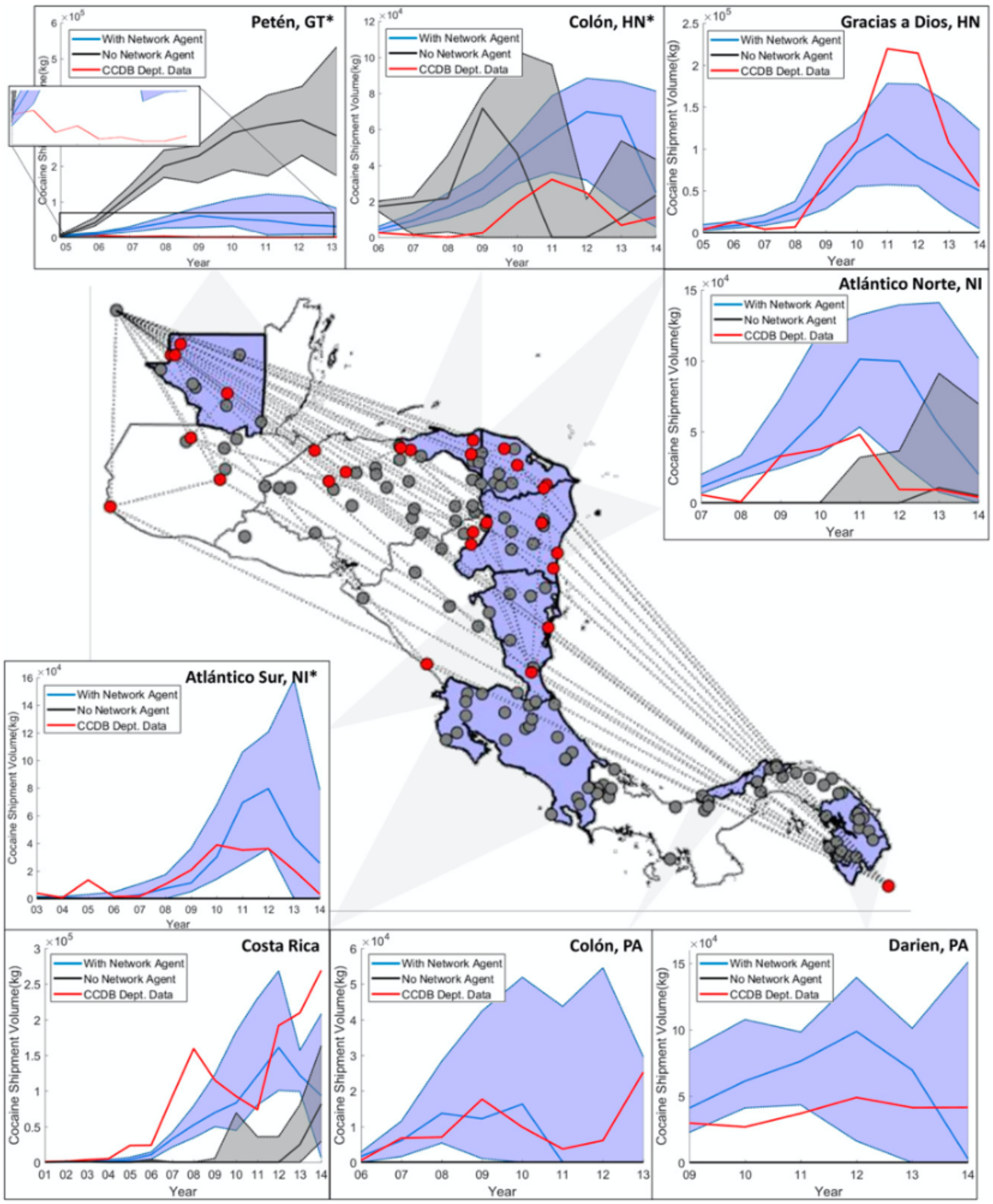

Figure 2: Central America modeling domain (center) with an example simulated narco-trafficking network consisting of inactive nodes (gray circles), active nodes (red circles), and trafficking routes between each active node (dashed lines). The most southern and northern nodes outside of the model domain represent supply (e.g., Colombia) and demanding nodes (e.g., Mexico), respectively. Around the periphery, comparisons of subnational cocaine shipment volumes (blue regions in the map) reported at the administrative level of departments

in the Consolidated Counterdrug Database (CCDB) (red line) and median volumes simulated by model versions with (blue line) and without (black line) a Network Agent. Shaded regions represent the bounds of the second and third quartiles of simulated cocaine volumes. Departments were selected to include at least one location per country and on the basis of having at least 5 y of continuous observations reported in CCDB. Image and legend from (Magliocca et al., 2019).

This study illustrates practice and promise in the golden age in many ways. First, their team consists of nine co-authors from seven universities, one government organization, and a coauthor who remained anonymous to protect confidential sources (and perhaps to stay alive). Their affiliations span geography, politics, biology, and earth sciences. Second, their model includes a novel application of ideas from behavioral economics about learning (Camerer & Ho, 1999) and salience (Bordalo, Gennaioli, & Shleifer, 2012) of specific trafficking events. Third, their model can be used to analyze how different policies will hypothetically change trafficking, prices, and drug use. Of course, models like this are never perfect, but they are a starting point and can always be improved using new evidence and plausible extensions.

In the next section, we present two more general “case studies” of successful interdisciplinarity-- behavioral economics and social network science. In both cases, interdisciplinary research led to the creation of new cross-disciplinary fields of inquiry built on the comparative advantages of contributing fields, inspiring a shared lingua franca, generating insights about human nature, and improving social outcomes.

2. Case Study: Behavioral Economics

Behavioral economics is the first of our two examples of successful interdisciplinary enterprises (Thaler, 2015, 2018). Behavioral economics uses evidence and methods from other social sciences -- particularly psychology -- to analyze natural limits on human computation, willpower, and selfishness. These analyses make new predictions about natural field data, including how markets work and can make novel suggestions about policies to improve human welfare.

Analyzing such limits was of interest because conventional rational choice theory assumes maximization of subjective values (“utilities”) and Bayesian integration of information, sometimes over a long-time horizon or accounting correctly for risks. Not all people are always that smart or patient.

To be fair, rational choice theory was always intended to be useful, rather than realistic. The question behavioral economists tackled was whether theories assuming more realistic psychology could be precise and *more* useful. Thaler and others (Camerer, Loewenstein, & Rabin, 2004) used an “insider” approach. This insider approach took rational choice theory as a simple benchmark, identified empirical “anomalies” that could not be sensibly explained by that benchmark, and sought explanations which added extra ingredients sparingly, to explain the anomalies and make new predictions. The first step was to begin with highly controlled laboratory experimental evidence (using hybrid methods from psychology and experimental economics) to convince skeptics and establish plausible alternative theories. Then we turned to make new predictions about field data. Alternative theories with a small number of added parameters were developed so that rational and behavioral predictions could be compared (DellaVigna, 2018).

Example #1: Loss aversion.

In their influential prospect theory, Kahneman and Tversky (1979, 1992) proposed that outcomes were subjectively valued by their gains and losses relative to a reference point, analogous to how a single percept could be subjectively perceived -- or "framed"-- as one of two distinct things (such as the face-vase illusion). For example, people may estimate their longevity to be higher if they judge the chance that they would live to age 75, compared to when they judged the chance that they would die before age 75 (Payne, Sagara, Shu, Appelt, & Johnson, 2013).

Tversky and Kahneman also suggested that losses were disliked much more than equal-sized gains, a phenomenon called "loss-aversion." Loss-aversion is sometimes conveniently expressed by a single parameter, λ, the ratio of gain utilities to loss utilities (or to their marginal utilities), which is often measured to be around 1.9 (Figure 2b).

Loss-aversion became part of explanations for many different phenomena in social science, such as (1) which kinds of financial risks people accept or dislike in lab experiments (Gneezy & Potters, 1997), (2) why stocks return so much more than bonds (Thaler & Benartzi, 2004), and (3) why there is a gap between high prices demanded to sell goods and lower prices paid to buy the same goods, the "endowment effect" (Kahneman, Knetsch, & Thaler, 1990). Psychologists demonstrated how sadness and disgust change the endowment effect (Lerner, Small, & Loewenstein, 2004) and also suggested effects of cognitive sequencing (Johnson, Häubl, & Keinan, 2007) and attention (Bhatia & Golman, 2019; Yechiam & Hochman, 2013). Cognitive neuroscientists have found evidence for loss-aversion in neural circuitry (Tom, Fox, Trepel, & Poldrack, 2007), including dissociations between circuitry valuing gains and losses (Yacubian et al., 2006) and an unusual *tolerance* of losses in patients with amygdala damage (De Martino, Camerer, & Adolphs, 2010). Political scientists have posited loss-aversion as one reason why concessions in bargaining are difficult (McDermott, 2004) and have analyzed its theoretical effects on election outcomes (Alesina & Passarelli, 2019) and trade policy (Tovar, 2009). Figure 2 illustrates estimates of loss-aversion along with applications from goal-setting at round numbers and "narrow bracketing" of local losses and gains that should, rationally, be added up.

Many behavioral economists have not been keenly interested in the evolutionary and cultural origins of phenomena like loss-aversion (an unfortunate omission, in our view). There is evidence that loss-aversion and endowment effects are present in monkeys (Lakshminaryanan, Chen, & Santos, 2008) and great apes (Kanngiesser, Santos, Hood, & Call, 2011) -- though only for food and not for other valued goods (e.g., tools). Apicella, Azevedo, Christakis and Fowler (2014) also found an unusual lack of endowment effects among market-isolated Hadza villagers in Tanzania. These data indicate that loss-aversion is not as universal as thought, and show why a wider scope of new data is needed.

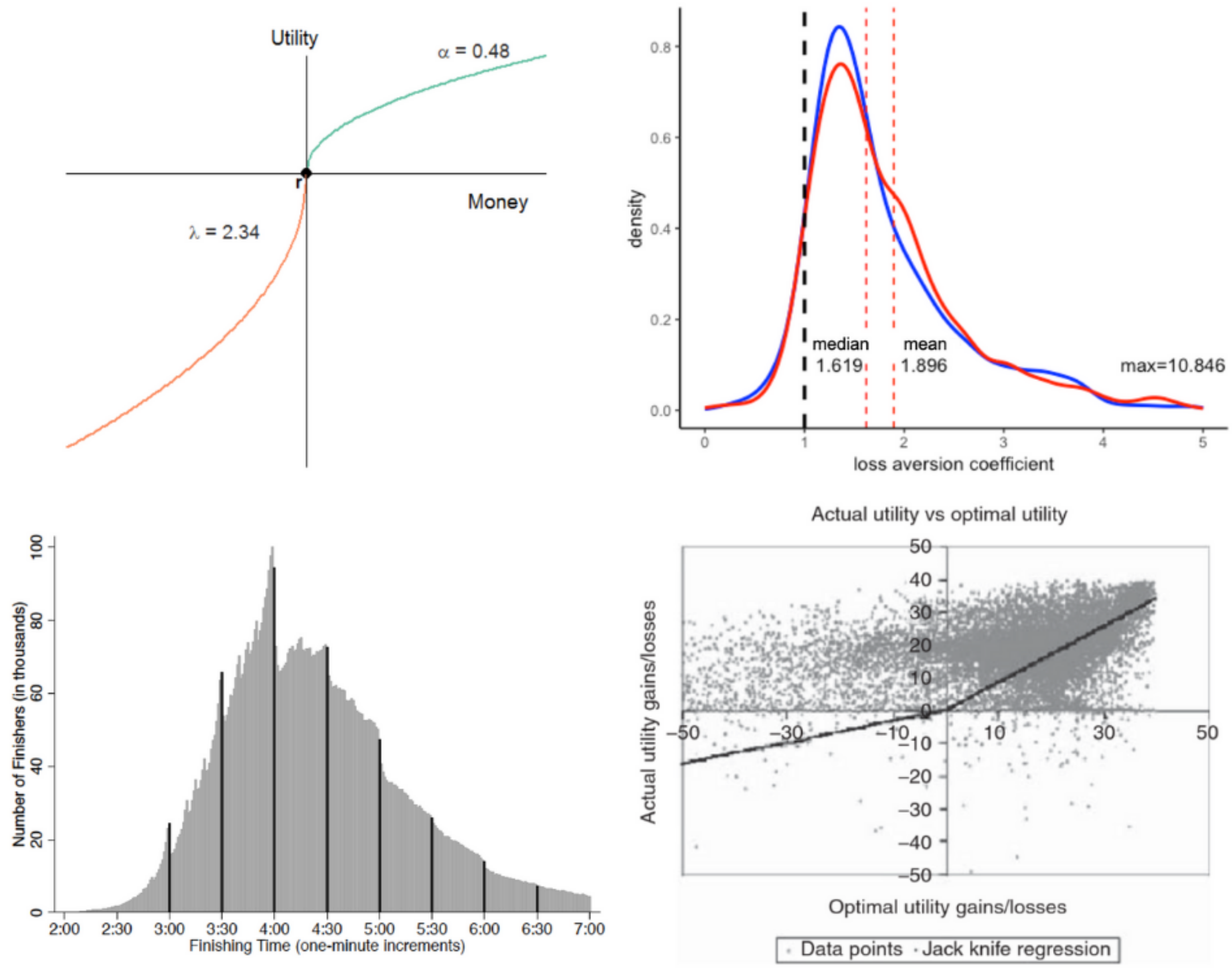

Figure 2: Loss-Aversion. (a) The gain-loss utility function over money derived from group parameters estimated from risky choices (Baillon, Bleichrodt, & Spinu, 2018). (b) The empirical distribution of the loss-aversion parameter λ from a meta-analysis. The blue and red panels include 286 and 469 effects, respectively (unpublished author data). (c) The distribution of marathon finishing times, with over nine million data points (Allen, Dechow, Pope, & Wu, 2017). Note the peaks at round numbers. (d) Actual point values in each period, plotted against optimal conditional point values from consumption choices, in a 50-period savings experiment (Brown, Chua, & Camerer, 2009). Note how few actual point values are negative even when optimal point values should be negative. This indicates that most subjects do not like to make choices that generate individual-period losses ("narrow bracketing"), even though performance is determined by the sum of all 50 periods.

Loss-aversion contributes to a “status quo bias,” the exaggerated tendency to choose a suggested default (or a previous status quo) when other choices are readily available (Samuelson & Zeckhauser, 1988). Countries in which organ donation is the default have much higher rates of donation than those in which it is not the default, even though the choice is simple to make (Johnson & Goldstein, 2003). The first impactful application of status quo bias is the “Save More Tomorrow” (SMART) plan (Thaler & Benartzi, 2004). In this plan, companies auto-enroll workers into tax-advantaged 401(k) plans and invest a fraction of their next pay raise into the plan (so their paycheck does not go down and creates a subjective loss). These plans have increased savings substantially, with no apparent reduction in savings from other sources (Chetty, Friedman, Leth-Petersen, Nielsen, & Olsen, 2014). The SMART plan became a poster child for many types of “nudges,” designed choices that help some people make better decisions than they are likely to make on their own (Camerer, Issacharoff, Loewenstein, O’Donoghue, & Rabin, 2003; Thaler & Sunstein, 2009).

Example #2: Social preferences

Humans are the most prosocial species--helping unrelated others at a cost to ourselves--and we alsoe create large-scale institutions to facilitate such prosocial behavior. Cutting across social sciences is the question of how to express this prosociality mathematically, and what data to collect. Behavioral economics contributed both theories and a menu of economic choices and games.

Of course, prosociality has long been contemplated in all social sciences, as well as in biology, moral philosophy, literature, and beyond. In economics, Adam Smith discussed “moral sentiments” and “fellow-feeling” (Smith, 1759). In 1881, Edgeworth included a “coefficient of effective sympathy”--the weight one person places on the utility of another--to try to make bargaining theory more precise (Edgeworth, 1881). That simple formulation and other variants (Loewenstein, Thompson, & Bazerman, 1989) are still used today. In the 1960s, social psychologists began to describe social value orientations in the style of psychometrics (Messick & McClintock, 1968) and distinguished importantly between equal outcomes and equitable ones, reflecting differences in need or inputs (Messick & Cook, 1983).

Game theory offers canonical strategic interactions that can be used to dissect elements of prosociality. A famous example is the “ultimatum game” (Camerer, 2003; Güth, Schmittberger, & Schwarze, 1982). In this game, a proposer offers a share of a known amount of resources, such as $10, to a responder. The responder can accept the offer, in which case bargaining ends and they collect their money, or the responder can reject it, and then they both get zero. Games like this can measure whether and why people will reject money and whether the proposer correctly anticipates rejection.

Rejecting a low ultimatum offer is now thought to show negative reciprocity--a willingness to sacrifice resources to harm another person who has been unfair (relative to a social norm, often with cultural content). This tendency is even evident at the collective level. For example, police effectively solve fewer criminal cases after losing a wage arbitration (Mas, 2006).

As the ultimatum game caught on across social sciences, other fascinating games quickly followed, each with a natural interpretation about psychological motives (Camerer & Fehr, 2004): (1) dictator allocations, in which the responder must accept the offer (measuring altruism and norm-sensitivity); (2) trust games, in which a first-mover invests money, with a social risk to potentially benefit both parties, gambling that the second-mover will share the total gain (Berg, Dickhaut, & McCabe, 1995; Camerer & Weigelt, 1988); and (3) many-person gift-exchange labor markets in which firms prepay wages and hope that workers exert costly effort which benefits the firms and repays their trust (DellaVigna & Pope, 2018; Ernst Fehr, Kirchsteiger, & Riedl, 1993).

Anthropologists also adopted these games. An interdisciplinary team, including anthropologists and behavioral economists, used economic games to study cross-cultural sociality in small-scale societies (Henrich et al., 2005, 2010). They learned that stronger sharing norms (which were punished by ultimatum rejections) were associated with societal cooperation, such as, building houses together, and with the extent of market trading.

As interest in these games grew, the sociological lingua franca of a "norm" got imported into other social sciences. Norms are informal social rules that are expected to be followed, and usually informally self-enforced by social punishment for deviations (even absent legal enforcement). In dictator allocation games, for example, people have different subjective norms about what is fair to share. Their sharing of actual money is closely tied to their norm perceptions (Krupka & Weber, 2009). Thus, sharing money seems to reflect "manners" consistent with perceived norms rather than altruism per se (Camerer & Thaler, 1995).

Cognitive neuroscientists have also used these games to measure social preferences, identify circuitry implementing prosociality (Tricomi, Rangel, Camerer, & O'Doherty, 2010), associate brain lesions with abnormal social preference (Krajbich, Adolphs, Tranel, Denburg, & Camerer, 2009), and linking to individual differences in neurotypical populations more generally (Bruhin, Fehr, & Schunk, 2019).

Knowing more about social preferences has not contributed immediately to solving social problems at the scale that "nudging" has. However, experiments have suggested social forces that could enhance prosociality. For example, allowing people to punish others who have behaved antisocially seems to increase cooperation (Fehr & Gächter, 2000; Yamagishi, 1986), although the results vary culturally (Herrmann, Thoni, & Gächter, 2008). New evidence has also invigorated understanding of charitable giving (DellaVigna, List, & Malmendier, 2012). In the future, diagnostic tools will likely emerge from a better understanding of sociality, with applications ranging from psychiatry, methods to develop empathy, and people analytics enhancing the matching of workers with jobs.

Summary:

Progress in understanding loss-aversion and social preferences in behavioral economics (and many intellectually neighboring fields) are two example illustrations of how interdisciplinarity and better measurement create progress and even help solve problems, in our golden age. The simple idea of loss-aversion came from perceptual psychology and compelling early data. There was substantial hostility to the idea of loss-aversion in mainstream economics for many years. The idea that people have preferences over what others get, familiar within social psychology, was less controversial, but there is still debate about the best general theory.

In general, behavioral economists won over skeptics by weaponizing the mantra that 'the easiest way to win an argument is to run another experiment or another statistical regression' (Thaler, 2018). In many areas of behavioral economics and finance, large data sets played an important role, including more recently, multi-site lab and field experiments (Cohn, Maréchal, Tannenbaum, & Zünd, 2019; Herrmann et al. 2008). A treasure trove of experimental data came about as nudges and other ideas were implemented by "behavioral insight teams" in firms, and governments on every continent, currently just over 200, according to the OECD ("Behavioural insights—OECD," n.d.) to create better outcomes for citizens and consumers (Halpern 2015).

As noted in discussing loss-aversion above, there has been limited interest of many behavioral economists in the deeper biological and cultural origins of preferences, norms, and cognitive limits. Such data and models are necessary to generalize ideas beyond activity in developed societies that are "WEIRD" (Henrich et al., 2005) and not representative of all human activity. How preferences are formed and changed is also central to essential discussions about the value of economic institutions, like market development (Bowles & Polanía-Reyes, 2012).

3. Case Study: Social Networks

Social networks are our second example of successful interdisciplinary enterprises. Network analysis uses methods from physics, computer science, and applied math to analyze questions often studied by sociologists, anthropologists, and psychologists regarding how interpersonal relationships are formed and how behaviors, beliefs, and emotions are transmitted across connected individuals (Watts & Dodds, 2007). One striking feature of network analysis is the diversity of scholars contributing to intellectual progress. People from different fields, traditions, and countries have worked together on related questions (Freeman, 2004). Network analysis has been significantly enabled by the availability of novel datasets, such as social media connections as well as increasingly "connected" devices, such as fitness trackers with social aspects (Aral & Nicolaides, 2017; Coviello et al., 2014; Phan & Airoldi, 2015).

The recent history of network analysis owes a lot to Watts & Strogatz (1998), who highlighted several key network properties, including that real networks are neither totally ordered nor random. However, it turned out that simple mathematical models could capture features of complex networks, and those models could be applied to network dynamics across a variety of phenomena. It turns out that the seemingly unrelated affiliations between actors, power grid transmission lines, and the neural network of *C. elegans* could all be captured via a simple "small-world" network model, a mathematical graph in which the nodes (individuals) are not neighbors with most of the other nodes, and yet all other nodes can be reached in a small number of steps (limited degrees of freedom connecting individuals) (Christakis & Fowler, 2011; Jackson, 2019; Watts, 2003, 2004).

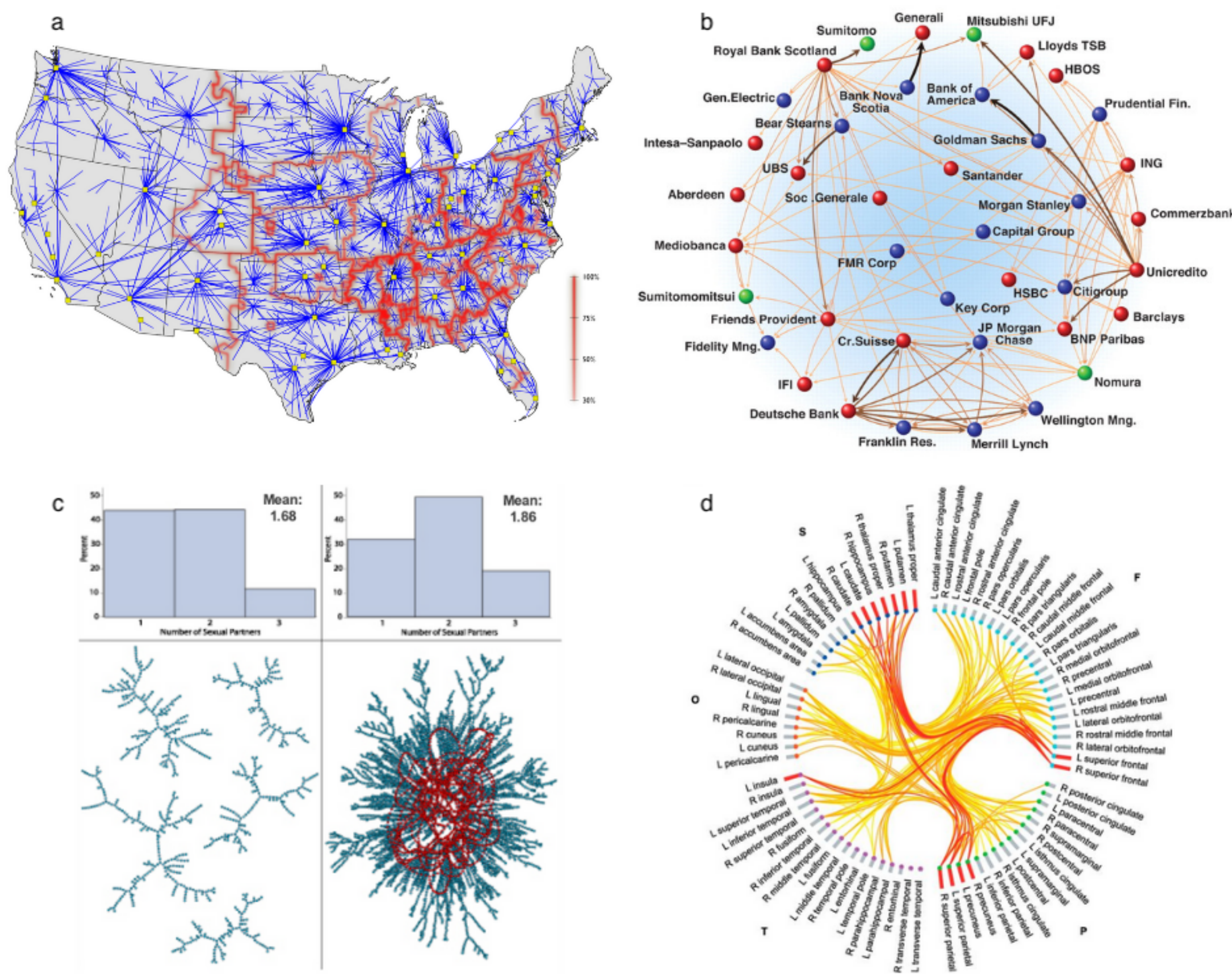

Figure 3: (a) A network of human traffic reveals cities that are important nodes (in yellow) and effective borders (in red) (Thiemann, Theis, Grady, Brune, & Brockmann, 2010). (b) A network of international financial institutions. Edges symbolize mutual share-holdings (Schweitzer et al., 2009). Note the high connectivity among nodes that can create systemic risk

and network vulnerability. (c) Effects of the distribution of sexual partner concurrency on network connectivity (adapted from Morris, Goodreau, & Moody, 2008). Note how a slight increase in average concurrent partners (from the top left to right histograms) dramatically impacts the number of nodes in the largest component of the network. (d) A network of brain regions where edges represent developmental increases in streamline density (Baker et al., 2015).

Example #1: Spread of Infectious Disease

Sociologists have been integral to guiding the development of these network models, given how ubiquitously they can help explain the spread of anything from disease to innovation (Davis & Greve, 1997). Most infectious diseases spread through human contact, making the study of infection a natural place to apply network analysis. One of the first and longest-used models of disease spread, known as the *SIR model*, was introduced by Kermack & McKendrick (1927) and included some highly oversimplified assumptions, including that individuals of different classes (i.e., infected vs. susceptible) connected exclusively in pairs, and that those connections occurred randomly.

As recounted by Martina Morris, it was feedback from a man in Uganda which illuminated the severe limitation of a model unable to handle multiple connections (multiple sexual partners) at once – something which is still closer to the norm than the exception in several societies (Kretzschmar & Morris, 1996). This insight led Morris and collaborators to create better models, ones which more accurately explained how the AIDS epidemic was spreading – specifically, how small variations in concurrency (simultaneous sexual partners) could have dramatic effects on a population's vulnerability to HIV (Morris & Kretzschmar, 1997).

It is unclear whether concurrency explains the full story, given that empirically it does not explain why places with high rates of concurrency do not necessarily have high rates of HIV and vice versa. One response to this is the potential misreporting regarding sexual activity, a private matter that complicates accurate data collection. Morris's team continues to collaborate across disciplines (with sociologists and statisticians – she is a professor of both), as well as across geographies (with several collaborators in Africa), to refine and improve models of the spread of infection, and apply them to new and better datasets.

Example #2: Revisiting Influence and Information Transmission

Several social science disciplines, from anthropology to political science, are particularly interested in collective decision making. While often studied at a static point in time, implicitly assuming that all individuals simultaneously make independent decisions, the heterogeneous process of information accumulation and integration prior to decision making suggests that decisions are actually made sequentially and that beliefs can be similarly "transmitted" from one individual to the next. The field of cultural evolution has been modeling information transmission for several decades, using both epidemiological and social network models in their approach (Richerson & Boyd, 1989).

Broadly, social contagion models allow simulating the speed at which individuals receive information and how past interactions influence their behavior (Watts & Dodds, 2007). These models focus on a handful of key parameters, which can be grouped as: (1) degree centrality, (2) eigenvector centrality, (3) diffusion centrality, and (4) bridging (Jackson, 2019). While one might *not* wish to be central in an HIV infection network, centrality is viewed as an advantage in most social networks and is correlated with financial success (Burt & Ronchi, 2007) and well-being (Morelli, Ong, Makati, Jackson, & Zaki, 2017). Degree centrality captures "popularity," the sheer number of connections an individual might have, capturing the speed at which these individuals can easily transmit information to a wide group at once. Eigenvector centrality, which captures how many well-connected others one is connected to, has been used to study social status and scapegoats (Weaverdyck & Parkinson, 2018). Diffusion centrality is a measure of "reach," capturing how well-positioned an individual is to spread and hear about information. Finally, bridging captures "social chameleons" who connect otherwise disparate groups. Interestingly, all of these positions appear to be context general: if an individual is central in one network, they are likely to be central in another, and so forth (Jackson, 2019).

Network analysis has therefore allowed researchers to apply new tools while revisiting old questions about social influence. For example, researchers have investigated whom individuals gravitate to in a network, finding that empathetic people are chosen for situations which require trust and support, while positive people are chosen for situations that are fun and exciting (Morelli et al., 2017). Other work has found that people give less money to those who are more socially distant (unknown) friends of friends in standard economic games (Candelo, Eckel, & Johnson, 2018; Goeree, McConnell, Mitchell, Tromp, & Yariv, 2010). Computational modeling methods have also been used to show that there is quicker consolidation of majority opinion and more successful spread of initially unpopular beliefs in populations characterized by their greater susceptibility to social influence (Muthukrishna & Schaller, 2019).

Given how many behaviors – from smoking to divorce – are "contagious" across individuals, the dynamics of such contagion are of immense interest to social scientists and non-social scientists alike.

Summary:

Network science would have been less successful without scientists from different disciplines borrowing ideas and communicating in a shared language about constructs and methods. To take a meta-perspective, innovation in network science has benefited from the wide network of researchers who share a lingua franca, can transmit high fidelity information, and bring a diversity of perspectives to the table (Muthukrishna & Henrich 2016).

Networks and their properties are fundamentally interesting because they underpin such a wide range of phenomena. Unlike behavioral economics, there was less conflict among those studying networks because the concept of a network was so obviously appealing and useful from the start (i.e., there was no interdisciplinary conflict about whether people "were networked" as occurred about whether people "were rational"). Furthermore, while sociologists studied networks first, the difficult question of what networks arise when people have scarce social bandwidth and can choose network links was cracked by economists (Jackson & Wolinsky, 1996). Moreover, the increasing availability of large, novel datasets that capture connections between individuals, such as social media and online communication data, has truly turbo-charged network science.

4. Spotlight on Studies

Table 1 displays twelve studies that epitomize the golden age of social science research (Salganik, 2018). Each of these papers is an excellent example of one or more of these features: (1) collaborating in an interdisciplinary team; (2) using new types of data; and (3) answering important and difficult questions. The table also demonstrates a wide variety of research topics, from exercise habits and social inequality to political preferences; and a diversity of datasets, including genetics, brain imaging, and browsing history. One notable study using CCTV footage tests the long-lived belief from early social psychology experiments that bystanders do not intervene to help strangers if there are other bystanders around (they actually do).

Summary	**Subfield(s)***	**Main Novelty**	**Reference**
Evolutionary changes in hominins created a niche that favored individuals with the ability to communicate and persuade, transforming sociopolitical life.	Anthropology, Political Science	Interdisciplinarity	(Gintis, van Schaik, & Boehm, 2015)
Greater exposure to war increases	Anthropology, Biology, Economics	Interdisciplinarity	(Henrich, Bauer, Cassar, Chytilová, &

religiosity.			Purzycki, 2019)
Rwandans use the mobile phone network to transfer “mobile money” to those affected by unexpected economic shocks.	Economics	New type of data: mobile phone usage	(Blumenstock, Fafchamps, & Eagle, 2011)
Describing the barriers to understanding the impact of AI on the labor market.	Economics	Interdisciplinarity	(Frank et al., 2019)
Railroad expansion from 1870 to 1890 in the U.S. increased agricultural land value.	Economic History	New type of data: geographic information system network database	(Donaldson & Hornbeck, 2016)
Brain responses to emotionally evocative images predict political ideology.	Political Science, Neuroscience, Psychiatry	Interdisciplinarity, new type of data: fMRI	(Ahn et al., 2014)
Genetic data can predict economic and political preferences.	Political Science, Economics, Psychology, Sociology	Interdisciplinarity, new type of data: GWAS	(Benjamin et al., 2012)
Musical preferences and personality traits are linked.	Psychology, Marketing	New type of data: Facebook likes	(Nave et al., 2018)
Bystanders will help in public conflict.	Psychology, Sociology	Interdisciplinarity, new type of data: CCTV footage	(Philpot, Liebst, Levine, Bernasco, & Lindegaard, 2019)
Social networks strongly influence exercise habits.	Sociology	New type of data: fitness tracking	(Aral & Nicolaides, 2017)
Fatal shootings of police officers increases police	Sociology	New type of data: NYC stop-and-frisk reports	(Legewie, 2016)

violence towards black suspects.			
Estimating social, environmental, and health inequalities with neural networks and street images.	Sociology, Economics	New type of data: street images	(Suel, Polak, Bennett, & Ezzati, 2019)

*As much as we admire those who cross disciplinary boundaries, making it difficult to identify home fields, authors' departmental affiliations are used here as a heuristic description.

5. Conclusion and Challenges

Interdisciplinary research inevitably presents new challenges. The following obstacles are worth noting given they disproportionately concern teams working on questions that cut across disciplines. It is advised that interdisciplinary research teams discuss and plan for dealing with these challenges before the research work begins:

- The question of **informatics**, or where and how information is accumulated, can be a special challenge for teams who are used to contributing to traditionally disparate disciplines. Many journals cater to the readership of a specific discipline or discipline subfield, with authors citing papers predominantly from like-minded journals. While cross-citation is on the rise, it is not guaranteed that interdisciplinary work will make equal contributions across fields, presenting the possibility of losing valuable insight with relevance to one of the fields.
- Closely tied to informatics is the question of **incentives and authorship**. Academics are often encouraged to remain focused on contributing to their respective subject areas, which means working with other academics in the same subfield and publishing in a specialized set of journals. While often practical and well-meaning advice, it constrains people to narrow paths with little upside to taking on interdisciplinary ventures. Furthermore, differences in authorship norms across disciplines (such as the strong emphasis on solo-authored papers in economics) make young researchers reluctant to join projects where a bigger team size is necessary in order to capture the range of specialized contributions necessary to tackle big research questions. If interdisciplinary work is to take off truly, research which makes contributions to other fields cannot be discounted, and papers with multiple co-authors should not automatically be seen as a smaller contribution than single-authored work.
- Interdisciplinarity possesses unique challenges for **"open science"**-- i.e., the sharing of procedures, data, and code intended to make research more widely accessible-- because different social science disciplines often have different tools and norms. As

Stodden et al. (2016) note, “Current reporting methods are often uneven, incomplete, and still evolving.” However, this challenge is now widely recognized, and efforts are underway to improve open science in practice.

· As mentioned in the introduction, interdisciplinary teams tend to work on big questions, applying a range of tools and insights to solve important, complex problems. A characteristic feature of these problems is their tendency to bring up novel concerns regarding individual **privacy and ethics**. New types of data – from genetics to real-time biofeedback – carry potentially sensitive information. Sensors have great promise for changing behavior and mitigating risk as a real-time physical nudge. However, they also present ethical quandaries, such as what happens if the sensors make a mistake or the nudge is overridden. Scientists take experimentation and transparency for granted, but the average citizen is more skeptical (Meyer et al., 2019). Interdisciplinary teams across social science should seek ethicists and legal scholars to join the conversation.

· Another challenge is the creation of **unifying frameworks** to explain behaviors across disciplines. Better theories will restrain the number of explanations that could be derived from big data by setting appropriate priors for hypotheses (Muthukrishna & Henrich, 2019). An expansion of methodological approaches alone will not increase scientific knowledge unless there is common lingua franca or, even better, genuinely unifying frameworks. Akin to the construction of modern biology from unifying principles in chemistry and physics, social science would benefit from evolutionarily plausible theories that provide ultimate (function) and proximate (mechanism) explanations. (Gintis, 2007) makes an argument that game theory is one promising candidate for unification.

The challenges of informatics, incentives, open science, ethics, and theoretical unification are serious. However, the same interdisciplinarity, creation of institutions, and reliance on better and more extensive data that make for our golden age should help solve these challenges too. Furthermore, there is reason to be optimistic: our increasingly connected age means that knowledge from other disciplines is much easier to access. Cross-disciplinary citations no longer require walking between libraries to find journals siloed in between the literal four walls of their own field!

It is foolish, of course, to forecast both a number and a time at which problems like the worldwide rise of obesity or “fake news” will be reined in. However, it is safe to say that our golden age will be marked by faster rates of progress in producing breakthrough social science and solutions to such human suffering than ever before.

Acknowledgments: We thank Fred Blum, Jonathan Katz, Joseph Henrich, Philip Hoffman, Scott Page, and Jerry Davis for helpful comments and discussions on related concepts in social science. We are grateful for the support of the T&C Chen Center (Fellowships for MG and AB, support for CFC), the Behavioral and Neuroeconomics Discovery Fund (for CFC), and especially Trilience (for CFC) for a longstanding interest in, and financial support of this topic.

Works Cited

Ahn, W.-Y., Kishida, K. T., Gu, X., Lohrenz, T., Harvey, A., Alford, J. R., … Montague, P. R. (2014). Nonpolitical Images Evoke Neural Predictors of Political Ideology. *Current Biology*, *24*(22), 2693–2699. https://doi.org/10.1016/j.cub.2014.09.050

Alesina, A., & Passarelli, F. (2019). Loss Aversion in Politics. *American Journal of Political Science*. https://doi.org/10.1111/ajps.12440

Allen, E. J., Dechow, P. M., Pope, D. G., & Wu, G. (2017). Reference-Dependent Preferences: Evidence from Marathon Runners. *Management Science*, *63*(6), 1657–1672. https://doi.org/10.1287/mnsc.2015.2417

Angrist, J., Azoulay, P., Ellison, G., Hill, R., & Lu, S. F. (2017). Inside Job or Deep Impact? Using Extramural Citations to Assess Economic Scholarship. *Journal of Economic Literature*. https://doi.org/10.3386/w23698

Apicella, C. L., Azevedo, E. M., Christakis, N. A., & Fowler, J. H. (2014). Evolutionary Origins of the Endowment Effect: Evidence from Hunter-Gatherers. *American Economic Review*, *104*(6), 1793–1805. https://doi.org/10.1257/aer.104.6.1793

Aral, S., & Nicolaides, C. (2017). Exercise contagion in a global social network. *Nature Communications*, *8*(1), 14753. https://doi.org/10.1038/ncomms14753

Baillon, A., Bleichrodt, H., & Spinu, V. (2018). *Searching for the Reference Point* [Working Paper]. Retrieved from https://aurelienbaillon.com/research/papers/pdf/reference_point.pdf

Baker, S. T. E., Lubman, D. I., Yucel, M., Allen, N. B., Whittle, S., Fulcher, B. D., … Fornito, A. (2015). Developmental Changes in Brain Network Hub Connectivity in Late Adolescence. *Journal of*

Neuroscience, *35*(24), 9078–9087. https://doi.org/10.1523/JNEUROSCI.5043-14.2015

Behavioural insights—OECD. (n.d.). Retrieved August 28, 2019, from Organisation for Economics Co-operation and Development website: https://www.oecd.org/gov/regulatory-policy/behavioural-insights.htm

Benjamin, D. J., Cesarini, D., van der Loos, M. J. H. M., Dawes, C. T., Koellinger, P. D., Magnusson, P. K. E., … Visscher, P. M. (2012). The genetic architecture of economic and political preferences. *Proceedings of the National Academy of Sciences*, *109*(21), 8026–8031. https://doi.org/10.1073/pnas.1120666109

Berg, J., Dickhaut, J., & McCabe, K. (1995). Trust, Reciprocity, and Social History. *Games and Economic Behavior*, *10*(1), 122–142. https://doi.org/10.1006/game.1995.1027

Bhatia, S., & Golman, R. (2019). Attention and reference dependence. *Decision*, *6*(2), 145–170. https://doi.org/10.1037/dec0000094

Blumenstock, J. E., Fafchamps, M., & Eagle, N. (2011). Risk and Reciprocity Over the Mobile Phone Network: Evidence from Rwanda. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1958042

Bordalo, P., Gennaioli, N., & Shleifer, A. (2012). Salience theory of choice under risk. *The Quarterly Journal of Economics*, *127*(3), 1243–1285.

Bowles, S., & Polanía-Reyes, S. (2012). Economic Incentives and Social Preferences: Substitutes or Complements? *Journal of Economic Literature*, *50*(2), 368–425. https://doi.org/10.1257/jel.50.2.368

Brown, A. L., Chua, Z. E., & Camerer, C. F. (2009). Learning and visceral temptation in dynamic saving experiments. *The Quarterly Journal of Economics*, *124*(1), 197–231.

Bruhin, A., Fehr, E., & Schunk, D. (2019). The many Faces of Human Sociality: Uncovering the Distribution and Stability of Social Preferences. *Journal of the European Economic Association*, *17*(4), 1025–1069. https://doi.org/10.1093/jeea/jvy018

Burt, R. S., & Ronchi, D. (2007). Teaching executives to see social capital: Results from a field experiment. *Social Science Research*, *36*(3), 1156–1183. https://doi.org/10.1016/j.ssresearch.2006.09.005

Camerer, C. (2003). Behavioural studies of strategic thinking in games. *Trends in Cognitive Sciences*, *7*(5), 225–231. https://doi.org/10.1016/S1364-6613(03)00094-9

Camerer, C., & Fehr, E. (2004). Measuring Social Norms and Preferences Using Experimental Games: A Guide for Social Scientists. In J. Henrich, R. Boyd, S. Bowles, C. Camerer, E. Fehr, & H. Gintis (Eds.), *Foundations of Human Sociality*. https://doi.org/10.1093/0199262055.001.0001

Camerer, C., & Ho, T. H. (1999). Experience-weighted Attraction Learning in Normal Form Games. *Econometrica*, *67*(4), 827–874. https://doi.org/10.1111/1468-0262.00054

Camerer, C., Issacharoff, S., Loewenstein, G., O'Donoghue, T., & Rabin, M. (2003). Regulation for Conservatives: Behavioral Economics and the Case for "Asymmetric Paternalism." *University of Pennsylvania Law Review*, *151*(3), 1211. https://doi.org/10.2307/3312889

Camerer, C., Loewenstein, G., & Rabin, M. (Eds.). (2004). *Advances in behavioral economics*. New York : Princeton, N.J: Russell Sage Foundation ; Princeton University Press.

Camerer, C., & Thaler, R. H. (1995). Anomalies: Ultimatums, Dictators and Manners. *Journal of Economic Perspectives*, *9*(2), 209–219. https://doi.org/10.1257/jep.9.2.209

Camerer, C., & Weigelt, K. (1988). Experimental Tests of a Sequential Equilibrium Reputation Model. *Econometrica*, *56*(1), 1. https://doi.org/10.2307/1911840

Candelo, N., Eckel, C., & Johnson, C. (2018). Social Distance Matters in Dictator Games: Evidence from 11 Mexican Villages. *Games*, *9*(4), 77. https://doi.org/10.3390/g9040077

Chetty, R., Friedman, J. N., Leth-Petersen, S., Nielsen, T. H., & Olsen, T. (2014). Active vs. Passive Decisions and Crowd-Out in Retirement Savings Accounts: Evidence from Denmark *. *The Quarterly Journal of Economics*, *129*(3), 1141–1219. https://doi.org/10.1093/qje/qju013

Christakis, N. A., & Fowler, J. H. (2011). *Connected: The surprising power of our social networks and how they shape our lives*. New York, NY: Little, Brown.

Cohn, A., Maréchal, M. A., Tannenbaum, D., & Zünd, C. L. (2019). Civic honesty around the globe.

Science, *365*(6448), 70–73. https://doi.org/10.1126/science.aau8712

Coviello, L., Sohn, Y., Kramer, A. D. I., Marlow, C., Franceschetti, M., Christakis, N. A., & Fowler, J. H. (2014). Detecting Emotional Contagion in Massive Social Networks. *PLoS ONE*, *9*(3), e90315. https://doi.org/10.1371/journal.pone.0090315

Davis, G. F., & Greve, H. R. (1997). Corporate Elite Networks and Governance Changes in the 1980s. *American Journal of Sociology*, *103*(1), 1–37. https://doi.org/10.1086/231170

De Martino, B., Camerer, C. F., & Adolphs, R. (2010). Amygdala damage eliminates monetary loss aversion. *Proceedings of the National Academy of Sciences*, *107*(8), 3788–3792.

DellaVigna, S. (2018). Structural Behavioral Economics. In *Handbook of Behavioral Economics: Applications and Foundations 1* (Vol. 1, pp. 613–723). https://doi.org/10.1016/bs.hesbe.2018.07.005

DellaVigna, S., List, J. A., & Malmendier, U. (2012). Testing for Altruism and Social Pressure in Charitable Giving. *The Quarterly Journal of Economics*, *127*(1), 1–56. https://doi.org/10.1093/qje/qjr050

DellaVigna, S., & Pope, D. G. (2018). What Motivates Effort? Evidence and Expert Forecasts. *The Review of Economic Studies*, *85*(2), 1029–1069. https://doi.org/10.1093/restud/rdx033

Donaldson, D., & Hornbeck, R. (2016). Railroads and American Economic Growth: A “Market Access” Approach. *The Quarterly Journal of Economics*, *131*(2), 799–858. https://doi.org/10.1093/qje/qjw002

Edgeworth, F. Y. (1881). *Mathematical Psychics: An Essay on the Application of Mathematics to the Moral Sciences*. Retrieved from https://books.google.com/books?id=StokAAAAMAAJ

Fehr, E., & Gächter, S. (2000). Cooperation and Punishment in Public Goods Experiments. *American Economic Review*, *90*(4), 980–994. https://doi.org/10.1257/aer.90.4.980

Fehr, E., Kirchsteiger, G., & Riedl, A. (1993). Does Fairness Prevent Market Clearing? An Experimental Investigation. *The Quarterly Journal of Economics*, *108*(2), 437–459. https://doi.org/10.2307/2118338

Frank, M. R., Autor, D., Bessen, J. E., Brynjolfsson, E., Cebrian, M., Deming, D. J., … Rahwan, I. (2019). Toward understanding the impact of artificial intelligence on labor. *Proceedings of the National Academy of Sciences*, *116*(14), 6531–6539. https://doi.org/10.1073/pnas.1900949116

Freeman, L. C. (2004). *The development of social network analysis: A study in the sociology of science*. Vancouver, BC : North Charleston, S.C: Empirical Press ; BookSurge.

Gintis, H. (2007). A framework for the unification of the behavioral sciences. *Behavioral and Brain Sciences*, *30*(1), 1–16. https://doi.org/10.1017/S0140525X07000581

Gintis, H., van Schaik, C., & Boehm, C. (2015). Zoon Politikon: The Evolutionary Origins of Human Political Systems. *Current Anthropology*, *56*(3), 327–353. https://doi.org/10.1086/681217

Gneezy, U., & Potters, J. (1997). An experiment on risk taking and evaluation periods. *The Quarterly Journal of Economics*, *112*(2), 631–645.

Goeree, J. K., McConnell, M. A., Mitchell, T., Tromp, T., & Yariv, L. (2010). The 1/d Law of Giving. *American Economic Journal: Microeconomics*, *2*(1), 183–203. https://doi.org/10.1257/mic.2.1.183

Güth, W., Schmittberger, R., & Schwarze, B. (1982). An experimental analysis of ultimatum bargaining. *Journal of Economic Behavior & Organization*, *3*(4), 367–388. https://doi.org/10.1016/0167-2681(82)90011-7

Henrich, J., Bauer, M., Cassar, A., Chytilová, J., & Purzycki, B. G. (2019). War increases religiosity. *Nature Human Behaviour*, *3*(2), 129–135. https://doi.org/10.1038/s41562-018-0512-3

Henrich, J., Boyd, R., Bowles, S., Camerer, C., Fehr, E., Gintis, H., … Tracer, D. (2005). “Economic man” in cross-cultural perspective: Behavioral experiments in 15 small-scale societies. *Behavioral and Brain Sciences*, *28*(6), 795–815. https://doi.org/10.1017/S0140525X05000142

Henrich, J., Ensminger, J., McElreath, R., Barr, A., Barrett, C., Bolyanatz, A., … Ziker, J. (2010). Markets, Religion, Community Size, and the Evolution of Fairness and Punishment. *Science*, *327*(5972), 1480–1484. https://doi.org/10.1126/science.1182238

Herrmann, B., Thoni, C., & Gächter, S. (2008). Antisocial Punishment Across Societies. *Science*, *319*(5868), 1362–1367. https://doi.org/10.1126/science.1153808

Jackson, M. O. (2019). *The human network: How your social position determines your power, beliefs, and behaviors* (First edition). New York: Pantheon Books.

Jackson, M. O., & Wolinsky, A. (1996). A Strategic Model of Social and Economic Networks. *Journal of Economic Theory*, *71*(1), 44–74. https://doi.org/10.1006/jeth.1996.0108

Johnson, E. J., & Goldstein, D. (2003). Do Defaults Save Lives? *Science*, *302*(5649), 1338–1339. https://doi.org/10.1126/science.1091721

Johnson, E. J., Häubl, G., & Keinan, A. (2007). Aspects of endowment: A query theory of value construction. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *33*(3), 461–474. https://doi.org/10.1037/0278-7393.33.3.461

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1990). Experimental Tests of the Endowment Effect and the Coase Theorem. *Journal of Political Economy*, *98*(6), 1325–1348.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, *47*(2), 263. https://doi.org/10.2307/1914185

Kanngiesser, P., Santos, L. R., Hood, B. M., & Call, J. (2011). The limits of endowment effects in great apes (Pan paniscus, Pan troglodytes, Gorilla gorilla, Pongo pygmaeus). *Journal of Comparative Psychology*, *125*(4), 436–445. https://doi.org/10.1037/a0024516

Kermack, W. O., & McKendrick, A. G. (1927). A Contribution to the Mathematical Theory of Epidemics. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *115*(772), 700–721. https://doi.org/10.1098/rspa.1927.0118

Krajbich, I., Adolphs, R., Tranel, D., Denburg, N. L., & Camerer, C. (2009). Economic Games Quantify Diminished Sense of Guilt in Patients with Damage to the Prefrontal Cortex. *Journal of Neuroscience*, *29*(7), 2188–2192. https://doi.org/10.1523/JNEUROSCI.5086-08.2009

Kretzschmar, M., & Morris, M. (1996). Measures of concurrency in networks and the spread of infectious disease. *Mathematical Biosciences*, *133*(2), 165–195. https://doi.org/10.1016/0025-5564(95)00093-3

Krupka, E., & Weber, R. A. (2009). The focusing and informational effects of norms on pro-social behavior. *Journal of Economic Psychology*, *30*(3), 307–320. https://doi.org/10.1016/j.joep.2008.11.005

Lakshminaryanan, V., Chen, M. K., & Santos, L. R. (2008). Endowment effect in capuchin monkeys. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, *363*(1511), 3837–3844.

Legewie, J. (2016). Racial Profiling and Use of Force in Police Stops: How Local Events Trigger Periods of Increased Discrimination. *American Journal of Sociology*, *122*(2), 379–424. https://doi.org/10.1086/687518

Lerner, J. S., Small, D. A., & Loewenstein, G. (2004). Heart Strings and Purse Strings. Carryover Effects of Emotions on Economic Decisions. *Psychological Science*, *15*(5), 337–341. https://doi.org/10.1111/j.0956-7976.2004.00679.x

Loewenstein, G. F., Thompson, L., & Bazerman, M. H. (1989). Social utility and decision making in interpersonal contexts. *Journal of Personality and Social Psychology*, *57*(3), 426–441. https://doi.org/10.1037/0022-3514.57.3.426

Magliocca, N. R., McSweeney, K., Sesnie, S. E., Tellman, E., Devine, J. A., Nielsen, E. A., … Wrathall, D. J. (2019). Modeling cocaine traffickers and counterdrug interdiction forces as a complex adaptive system. *Proceedings of the National Academy of Sciences*, *116*(16), 7784–7792. https://doi.org/10.1073/pnas.1812459116

Mas, A. (2006). Pay, Reference Points, and Police Performance*. *Quarterly Journal of Economics*, *121*(3), 783–821. https://doi.org/10.1162/qjec.121.3.783

McDermott, R. (2004). Prospect Theory in Political Science: Gains and Losses From the First Decade. *Political Psychology*, *25*(2), 289–312. https://doi.org/10.1111/j.1467-9221.2004.00372.x

Messick, D. M., & Cook, K. S. (Eds.). (1983). *Equity theory: Psychological and sociological perspectives*. New York, N.Y: Praeger.

Messick, D. M., & McClintock, C. G. (1968). Motivational bases of choice in experimental games.

Journal of Experimental Social Psychology, *4*(1), 1–25. https://doi.org/10.1016/0022-1031(68)90046-2

Meyer, M. N., Heck, P. R., Holtzman, G. S., Anderson, S. M., Cai, W., Watts, D. J., & Chabris, C. F. (2019). Objecting to experiments that compare two unobjectionable policies or treatments. *Proceedings of the National Academy of Sciences*, *116*(22), 10723–10728. https://doi.org/10.1073/pnas.1820701116

Morelli, S. A., Ong, D. C., Makati, R., Jackson, M. O., & Zaki, J. (2017). Empathy and well-being correlate with centrality in different social networks. *Proceedings of the National Academy of Sciences*, *114*(37), 9843–9847. https://doi.org/10.1073/pnas.1702155114

Morris, M., Goodreau, S., & Moody, J. (2008). Sexual Networks, Concurrency, and STD/HIV. In K. K. Holmes (Ed.), *Sexually transmitted diseases* (4th ed, pp. 109–125). New York: McGraw-Hill Medical.

Morris, M., & Kretzschmar, M. (1997). Concurrent partnerships and the spread of HIV: *AIDS*, *11*(5), 641–648. https://doi.org/10.1097/00002030-199705000-00012

Muthukrishna, M., & Schaller, M. (2019). Are Collectivistic Cultures More Prone to Rapid Transformation? Computational Models of Cross-Cultural Differences, Social Network Structure, Dynamic Social Influence, and Cultural Change. *Personality and Social Psychology Review*, 108886831985578. https://doi.org/10.1177/1088868319855783

Nave, G., Minxha, J., Greenberg, D. M., Kosinski, M., Stillwell, D., & Rentfrow, J. (2018). Musical Preferences Predict Personality: Evidence From Active Listening and Facebook Likes. *Psychological Science*, *29*(7), 1145–1158. https://doi.org/10.1177/0956797618761659

Payne, J. W., Sagara, N., Shu, S. B., Appelt, K. C., & Johnson, E. J. (2013). Life expectancy as a constructed belief: Evidence of a live-to or die-by framing effect. *Journal of Risk and Uncertainty*, *46*(1), 27–50.

Phan, T. Q., & Airoldi, E. M. (2015). A natural experiment of social network formation and dynamics. *Proceedings of the National Academy of Sciences*, *112*(21), 6595–6600.

https://doi.org/10.1073/pnas.1404770112

Philpot, R., Liebst, L. S., Levine, M., Bernasco, W., & Lindegaard, M. R. (2019). Would I be helped? Cross-national CCTV footage shows that intervention is the norm in public conflicts. *American Psychologist*. https://doi.org/10.1037/amp0000469

Richerson, P. J., & Boyd, R. (1989). The role of evolved predispositions in cultural evolution. *Ethology and Sociobiology*, *10*(1–3), 195–219. https://doi.org/10.1016/0162-3095(89)90019-8

Salganik, M. J. (2018). *Bit by bit: Social research in the digital age*. Princeton: Princeton University Press.

Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of Risk and Uncertainty*, *1*(1), 7–59. https://doi.org/10.1007/BF00055564

Schweitzer, F., Fagiolo, G., Sornette, D., Vega-Redondo, F., Vespignani, A., & White, D. R. (2009). Economic Networks: The New Challenges. *Science*, *325*(5939), 422–425. https://doi.org/10.1126/science.1173644

Smith, A. (1759). *The Theory of Moral Sentiments*. McMaster University Archive for the History of Economic Thought.

Suel, E., Polak, J. W., Bennett, J. E., & Ezzati, M. (2019). Measuring social, environmental and health inequalities using deep learning and street imagery. *Scientific Reports*, *9*(1), 6229. https://doi.org/10.1038/s41598-019-42036-w

Thaler, R. H. (2015). *Misbehaving: The making of behavioral economics*. Retrieved from https://www.overdrive.com/search?q=F1484CE2-43BC-4DA9-A850-4279E96BFAF8

Thaler, R. H. (2018). From Cashews to Nudges: The Evolution of Behavioral Economics. *American Economic Review*, *108*(6), 1265–1287. https://doi.org/10.1257/aer.108.6.1265

Thaler, R. H., & Benartzi, S. (2004). Save More Tomorrow™: Using Behavioral Economics to Increase Employee Saving. *Journal of Political Economy*, *112*(S1), S164–S187. https://doi.org/10.1086/380085

Thaler, R. H., & Sunstein, C. R. (2009). *Nudge: Improving decisions about health, wealth, and happiness*

(Rev. and expanded ed). New York: Penguin Books.

Thiemann, C., Theis, F., Grady, D., Brune, R., & Brockmann, D. (2010). The Structure of Borders in a Small World. *PLoS ONE*, *5*(11), e15422. https://doi.org/10.1371/journal.pone.0015422

Tom, S. M., Fox, C. R., Trepel, C., & Poldrack, R. A. (2007). The neural basis of loss aversion in decision-making under risk. *Science*, *315*(5811), 515–518.

Tovar, P. (2009). The effects of loss aversion on trade policy: Theory and evidence. *Journal of International Economics*, *78*(1), 154–167. https://doi.org/10.1016/j.jinteco.2009.01.012

Tricomi, E., Rangel, A., Camerer, C., & O'Doherty, J. P. (2010). Neural evidence for inequality-averse social preferences. *Nature*, *463*(7284), 1089–1091. https://doi.org/10.1038/nature08785

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, *5*(4), 297–323.

Watts, D. J. (2003). *Six degrees: The science of a connected age* (1st ed). New York: Norton.

Watts, D. J. (2004). The "New" Science of Networks. *Annual Review of Sociology*, *30*(1), 243–270. https://doi.org/10.1146/annurev.soc.30.020404.104342

Watts, D. J. (2017). Should social science be more solution-oriented? *Nature Human Behaviour*, *1*(1), 0015. https://doi.org/10.1038/s41562-016-0015

Watts, D. J., & Dodds, P. S. (2007). Influentials, Networks, and Public Opinion Formation. *Journal of Consumer Research*, *34*(4), 441–458. https://doi.org/10.1086/518527

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world' networks. *Nature*, *393*(6684), 440–442. https://doi.org/10.1038/30918

Weaverdyck, M. E., & Parkinson, C. (2018). The neural representation of social networks. *Current Opinion in Psychology*, *24*, 58–66. https://doi.org/10.1016/j.copsyc.2018.05.009

Yacubian, J., Gläscher, J., Schroeder, K., Sommer, T., Braus, D. F., & Büchel, C. (2006). Dissociable systems for gain-and loss-related value predictions and errors of prediction in the human brain. *Journal of Neuroscience*, *26*(37), 9530–9537.

Yamagishi, T. (1986). The provision of a sanctioning system as a public good. *Journal of Personality and*

Social Psychology, *51*(1), 110–116. https://doi.org/10.1037/0022-3514.51.1.110

Yechiam, E., & Hochman, G. (2013). Losses as modulators of attention: Review and analysis of the unique effects of losses over gains. *Psychological Bulletin*, *139*(2), 497–518. https://doi.org/10.1037/a0029383